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ECO No. 98/21

EUI WORKING PAPERS

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ECONOMICS DEPARTMENT

EUI Working Paper **ECO** No. 98/21

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BADIA FIESOLANA, SAN DOMENICO (FI)

Printed in Italy in July 1998
European University Institute
Badia Fiesolana
I – 50016 San Domenico (FI)
Italy

NELSON AND PLOSSER REVISITED: EVIDENCE FROM FRACTIONAL ARIMA MODELS

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March 1998

ABSTRACT

Fractionally integrated ARMA (ARFIMA) models are investigated in an extended version of Nelson and Plosser's (1982) data set. The analysis is carried out using Sowell's (1992) procedure of estimating by maximum likelihood in the time domain. A crucial fact when estimating with parametric approaches is that the model must be correctly specified. Otherwise, the estimates are liable to be inconsistent. A model-selection procedure based on diagnostic tests on the residuals, along with likelihood criterions is adopted to determine the correct specification of each series. The results suggest that all series except unemployment rate and bond yield are integrated of order greater than one. Thus, the standard approach of taking first differences may lead to stationary series with long memory behaviour.

JEL classification: C22.

Key words: Nonstationarity, macroeconomic time series, long memory, ARFIMA models.

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1. Introduction

It is broadly accepted than one feature of macroeconomic time series is that the level of the series evolves or change with time, although in a rather smooth fashion. A common practice to explain and model these smooth movements was to assume that the series fluctuate around a deterministic trend, via a polynomial and/or a trigonometric function of time, which are fitted by linear regression techniques. A second way came after Nelson and Plosser's (1982) influential work, who following the work and ideas of Box and Jenkins (1970), argued that these fluctuations in the level were better explained by means of the so-called unit roots, or in other words, that the change in level is "stochastic" rather than "deterministic". Both "schools" try to model this persistent trend-cycle behaviour of the data although from a different perspective.

Mandelbrot (1969) and Mandelbrot and co-authors discussed a third way of explaining these fluctuations in the level. He argued that while many macroeconomic series exhibit a persistent trend-cyclical behaviour for a stretch of the data, when the same data is examined for a longer period, the persistent behaviour tends to disappear. The same type of behaviour was observed in other areas, notably in hydrology, and called the Hurst effect, in honour of the hydrologist Hurst, (Hurst (1951), (1957)), who, studying the records in the level of the river Nile, noticed that kind of pattern in its behaviour. In particular he noticed that the autocorrelation took far longer to decay to zero than the exponential rate associated with the autoregressive moving average (ARMA) class of models. These kind of models are called long memory, due to their ability to display significant dependence between distant observations in time.

Given a discrete covariance stationary time series process, say $\{x_t\}$, with autocovariance function $E(x_t-Ex_t)(x_{t-j}-Ex_t) = \gamma_j$, according to McLeod and Hipel (1978), the process is long memory if

$$\lim_{T\to\infty} \sum_{j=-T}^{j=T} |\gamma_j|$$

is infinite. A second way of characterize this type of processes is in the frequency domain. For that purpose, suppose that $\{x_t\}$ has absolute continuous spectral distribution, so that it has a spectral density function, denoted $f(\lambda)$, and defined as

$$\gamma_j = \int_{-\pi}^{\pi} f(\lambda) \cos j d\lambda, \qquad j = 0, \pm 1, \pm 2, \dots .$$

Thus, we can say that x_t displays the property of long memory if the spectral density function has a pole at some frequency λ in the interval $(0,\pi]$. One model, very popular amongst econometricians, capable of explaining this feature is the so-called fractionally integrated. A popular technique to analyze this model is through the fractional differencing ∇^d, where

$$\nabla^d = (1-L)^d = \sum_{k=0}^{\infty} (-1)^k \binom{d}{k} L^k,$$

and L is the lag operator. To illustrate this in case of a scalar time series x_t, $t=1,2...$, suppose that u_t is an unobservable covariance stationary sequence with spectral density that is bounded and bounded away from zero at any frequency, and

$$(1-L)^d x_t = u_t, \qquad t = 1,2,.... \tag{1}$$

The process u_t could itself be a stationary and invertible ARMA sequence, when its autocovariances decay exponentially, however, they could decay much slower than exponentially. When $d = 0$ in (1), $x_t = u_t$ and thus, x_t is 'weakly autocorrelated', also termed 'weakly dependent'. If $0 < d < 1/2$, x_t is still stationary, but its lag-j autocovariance γ_j decreases very slowly, like the power law j^{2d-1} as $j \to \infty$ and so the γ_j are non-summable. We say then that x_t has long memory given that its spectral density $f(\lambda)$ is unbounded at the origin. It may also be shown that these kind of processes satisfy

$$\gamma_j \sim c_1 j^{2d-1} \quad as \ j \to \infty \quad for \ |c_1| < \infty, \tag{2}$$

and

$$f(\lambda) \sim c_2 \lambda^{-2d} \quad as \ j \to 0^+ \quad for \ 0 < c_2 < \infty, \tag{3}$$

where the symbol ~ means that the ratio of the left hand side and the right hand side tends to 1, as $j \to \infty$ in (2), and as $\lambda \to 0^+$ in (3). Conditions (2) and (3) are not always equivalent but Zygmund (1995), and more generally Yong (1974) give conditions under which both expressions are equivalent. Finally as d in (1) increases beyond 1/2 and through 1 (the unit root case), x_t can be viewed as becoming "more nonstationary" in the sense, for example, that the variance of the partial sums increases in magnitude. This is also true for $d > 1$, so a large class of nonstationary process may be described by (1) (or (4) below) with $d \geq 1/2$. Processes like (1) with positive non-integer d are called fractionally integrated and when u_t is ARMA(p,q), x_t has been called a fractional ARIMA (ARFIMA(p,d,q)) process. Thus the model becomes

$$\phi(L)(1-L)^d x_t = \theta(L)\epsilon_t, \qquad t = 1,2,..., \tag{4}$$

where ϕ and θ are polynomials of orders p and q respectively, with all zeroes of $\phi(L)$ outside the unit circle, and all zeros of $\theta(L)$ outside or on the unit circle, and ε_t white noise. These kind of models were introduced by Granger and Joyeux (1980), Granger (1980, 1981) and Hosking (1981), (although earlier work by Adenstedt (1974) and Taqqu (1975) shows an awareness of the representation), and were justified theoretically in terms of aggregation by Robinson (1978) and Granger (1980).

In view of the preceding remarks there is some interest in estimating the fractional differencing parameter d, along with the other parameters related with the ARMA representation. Sowell (1992) analyzed in the time domain the exact maximum likelihood estimates of the parameters of a fractional ARIMA model (4), using a recursive procedure that allow quick evaluation of the likelihood function. We will employ this procedure in the empirical applications of Section 3.

In this article I claim that many macroeconomic time series may be well described by means of fractional ARIMA models and show that the classical trend-stationary (I(0)) and unit roots (I(1)) representations may be too restrictive with respect to the low-frequency dynamics of the series. Section 2 briefly summarizes some of the main results found in the literature involving Nelson and Plosser's (1982) data set. In Section 3 we estimate ARFIMA models for each of the series in an extended version of this data set, and finally Section 4 contains some concluding remarks.

2. Summary of the literature on Nelson and Plosser's (1982) data set

Nelson and Plosser (1982), in a classic paper, analyzed fourteen annual macroeconomic time series for the U.S. to find whether they were better characterized as trend-stationary or difference-stationary processes. These series started from 1860 to 1909 and ended in 1970, and they analyzed the logged series in all but one of these cases. Applying tests of Fuller (1976), Dickey and Fuller (1979), they reported strong evidence of unit roots. Let x_t, t = 1,2,... be the series to be studied. The unit-root model tested by Nelson and Plosser (1982) was essentially

$$(1-L)\,x_t = \alpha + u_t, \qquad t = 1,2,... \tag{5}$$

where

$$\phi(L)\,u_t = \epsilon_t, \qquad t = 1,2,..., \tag{6}$$

in which ϕ is a pth. degree polynomial, all of whose zeroes lie outside the unit circle, and ε_t is a white noise sequence. In the terminology of Box and Jenkins (1970), (5) and (6) constitute an ARIMA(p,1,0) model. Nelson and Plosser (1982) nested (5) in

$$(1-\rho L)x_t = \alpha + \beta t + u_t, \qquad t = 1,2,.... \tag{7}$$

where the null hypothesis corresponds to

$$H_o: \quad \rho = 1 \quad \mathit{and} \quad \beta = 0 \tag{8}$$

whereas $|\rho| < 1$ corresponds to a trend-stationary model. For various p in (6), the tests failed to reject the unit root null (5) in all except unemployment rate.

The paper of Nelson and Plosser (1982) has led to much subsequent research. Stock (1991) provided asymptotic confidence intervals for the largest autoregressive root of a time series when this root was close to one. When applied to Nelson and Plosser's (1982) data, his main conclusion was that the confidence interval were typically wide, containing the unit root for all series except unemployment and bond yield, though also including values significantly different from one. Perron (1988) analyzed the same data set, using tests of Phillips (1987), Phillips and Perron (1988), which more generally, are valid in the context of non-parametric autocorrelation, and came to reassess the findings of Nelson and Plosser (1982) in favour of unit roots. In fact, all series except unemployment rate and possibly industrial production may be characterized by the presence of a unit root, with or without a drift.

Kwiatkowski et al. (1992), observed that taking the null hypothesis to be I(1) rather than I(0) might lead to a bias in favour of the unit-root hypothesis; they proposed a I(0) test which formulates the null as a zero variance in a random walk, and applied it to the Nelson and Plosser (1982) data. Their conclusions can be summarized as follows: unemployment rate appears to be I(0) stationary; four series (consumer prices, real wages, velocity and stock prices) appear to have unit roots; three series (real G.N.P., nominal G.N.P. and bond yield) could possibly have as well a unit root; and for the remaining seven series they could not reject either the unit root or the trend-stationary representation.

Bayesian procedures have also been implemented. DeJong and Whitemann (1989) conducted empirical research with flat prior Bayesian techniques and challenged unit root finding in many cases, including Nelson and Plosser's (1982) series. They concluded that for many of these series, the trend-stationary hypothesis was much more likely. Similar results were obtained in DeJong et al. (1992). However, Phillips (1991), using objective ignorance priors, rather than flat priors, obtained results closely related to those obtained by the classical methods: seven of Nelson and Plosser's (1982) series showed evidence of unit roots.

The presence of structural break on these data has also been taking into account by several authors. Perron (1989) found that the Dickey and Fuller (1979) tests were invalid if the true alternative were that of trend-stationarity with a structural break. He proposed new tests and found that in ten out of the fourteen series, the unit root null was rejected. He treated the break as exogenous. Zivot and Andrews (1992) proposed a variation of his tests, allowing the structural break to be endogenous, finding less evidence against the unit roots as Perron (1989) did. Stock (1994) applied a Bayesian procedure that consistently classifies the stochastic component of a series as I(1) or I(0), applying it to Nelson and Plosser's (1982) data with both linear detrending and piecewise linear detrending, supporting their conclusions in the former, but not the latter, case.

In relation to fractional models, Gil-Alaña and Robinson (1997) analyzed an extended version of this data set by means of fractional integration analysis, using Robinson's (1994) tests for testing unit roots and other hypotheses. These tests allow to consider the unit root (I(1)) and the trend-stationary (I(0)) hypotheses as particular cases of I(d) processes. Their results varied substantially across the series and across various models for the I(0) disturbances, but practically all series appear to be nonstationary with d greater than 0.5.

3. Empirical applications

In this section we analyze the extended version of Nelson and Plosser's (1982) data by means of fractionally integrated ARMA models. As with their original data, the starting date is 1860 for consumer prices and industrial production; 1869 for velocity; 1871 for stock prices; 1889 for G.N.P. deflator and money stock; 1890 for employment and unemployment rate; 1890 for bond yield, real wages and wages; and 1909 for nominal and real G.N.P. and G.N.P. per capita. All the series except bond yield are transformed to natural logarithms and all ends in 1988. We estimate for each series different ARFIMA(p,d,q) models with p and q smaller than or equal to three, using the Sowell's (1992) procedure of estimating by maximum likelihood in the time domain.[1] In order to assure white noise residuals, several tests will be performed in each model, in particular, we will apply tests of normality, heteroscedasticity, autoregressive conditional heteroscedasticity (ARCH) and Lunj & Box tests.

Table 1 summarizes the estimated d's for the different ARMA representations in each series. We observe that in all them, the values of d are greater than 1, except unemployment rate (where all values are smaller than 1) and in some cases for velocity and bond yield. In all except four series, the difference between the minimum and the maximum value of d is smaller than 0.4 points, the main exception being again unemployment rate, with d ranging from -1.45 through 0.87. We also observe that money stock, wages, G.N.P. deflator, nominal G.N.P. and consumer prices appear to be the most nonstationary series, with d ranging from 1.21 through 1.49. On the other hand, unemployment rate, followed by bond yield appear as the less nonstationary ones, with d ranging between 0.87 and 1.17 in the latter series. Similar conclusions were obtained in Gil-Alaña and Robinson (1997) when applying Robinson's (1994) tests on these series. As a final remark in this table, we should mention that only in six out of the fourteen series we found at least one model where the residuals passed all the diagnostic tests at the 1% significance level. Most of the models failed to pass the tests of normality, mainly because of the presence of an outlier due to War World II. Table 2 corresponds to Table 1, based only on post-war data.

(Tables 1 and 2 about here)

Results are similar to those in Table 1, with all values of d greater than 1 except for unemployment rate, and in some cases for velocity and bond yield. The latter is the only series where we are unable to fit a model, passing all the diagnostic tests on the residuals at the 1% level, the problem now coming because of the presence of heteroscedastic residuals. As in Table 1, money stock, nominal G.N.P., consumer prices, wages and G.N.P. deflator appear as the most nonstationary series, while unemployment rate, followed by velocity and bond yield are the closest to stationarity.

As mentioned above, all these models were estimated by maximum likelihood. A crucial fact when estimating with parametric approaches is that the model must be correctly specified; if it is misspecified, the estimates of d are

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[1] To assure stationary, and following standard practice, the models are estimated in first differences and then converted back to levels.

liable to be inconsistent. In fact, misspecification of the short run components of the series can invalidate the estimation of its long run behaviour. In order to analyze which might be the best model specification for each of the series we proceed as follows: in those series in Table 1 where we found models passing all the diagnostic tests on the residuals, we take these models and analyze them carefully, through a model-selection criteria based on LR tests along with the Akaike (AIC) and Schwarz (SIC) information criterions. (It should be borne in mind that the AIC and SIC may not necessarily be the best criterions for applications involving fractional differences, see e.g. Hosking (1981)). In those series which failed to pass the tests in Table 1, we concentrate on the post-war data, carrying on the same analysis. Each of the series has its corresponding table according to the number of the sub-section. We start by examining the first of these series.

3.a Real G.N.P.

We observe eight models which pass the diagnostic tests on the residuals at the 1% significance level. The results are given in Table 3a. The values of d range between 1.17 and 1.49, rejecting the null of d = 0 in all cases, and the unit root null in five. The most general specifications describing the short run dynamics in this series are the ARMA(2,2) and the ARMA(3,1) models. In the former, the second moving average component is not significantly different from zero, and in the latter, the last two coefficients in the AR representation are also insignificant. Going backwards from the ARMA(3,1) model to an ARMA(1,1), a LR test rejects the former in favour of the latter, but the two coefficients are now close to zero.[2] Deleting here the MA coefficient, the AR(1) model has an insignificant coefficient, but deleting the AR parameter, the MA(1) model seems adequate to describe the data. If we move from an ARMA(3,1) to an AR(3) model, a LR test indicates that the latter model is preferred but the last two coefficients in the AR representation are insignificantly different from zero. Comparing the ARMA(2,2) with the AR(2) specification, the former seems preferred but the second AR and the second MA coefficients are again close to zero. Similarly, the AR(1) model gives an insignificant coefficient. In view of these results, it seems that the best two model specifications describing the short-run dynamics in this series might be a white noise and a MA(1) model. The AIC suggests the MA(1) model but the SIC indicates that the white noise specification might be more appropriate. Performing a LR test in order to choose between these two models, the white noise specification seems preferred. In addition, the standard error of d is smaller under this final parameterization.

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[2] In order to keep coherency with the previous tests, all the LR tests in this section are calculated at the 1% significance level.

Thus, we can conclude the analysis of this series by saying that the real G.N.P. can be well described as an ARIMA(0, 1.30, 0) model.

(Tables 3.a and 3.b about here)

3.b Real per capita G.N.P.

We observe in this series nine models with the residuals being possibly white noise. The most general specification is an ARMA(3,2) but we see that all the AR and the second MA coefficients are insignificantly different from zero. Looking at the ARMA(3,1) model, the values are very similar to the previous case, with smaller standard errors, though we still observe non-significant values at the second and third AR coefficients. A LR test suggests that the ARMA(1,1) model might be preferred but both coefficients in this model are now insignificant. Suppressing any of these two coefficients, both, the AR(1) and the MA(1) models seem appropriate. The AR(3) and the AR(2) models are both inadequate in view of the t-values. On the other hand, comparing the ARMA(3,2) with the ARMA(2,2), the latter seems preferred, with all the coefficients highly significant. Thus, we have three models that might be appropriate in this series: the ARMA(2,2), the AR(1) and the MA(1). The AIC indicates that the ARMA(2,2) model is the best specification, but the SIC, leading to a less heavily parameterized model, suggests the AR(1) representation. We have chosen the ARMA(2,2) since the standard errors are smaller in this model and the AIC gives the highest value across the different models presented in this table. A visual inspection of the residuals also corroborates this view, finding the closest residuals to white noise under this final parameterization. We therefore conclude by saying that the best model specification in this series might be an ARIMA(2, 1.11, 2) model.

3.c Employment

Six models are selected in this series and the range of values of d narrows from 1.14 to 1.22. We observe in all these models that the coefficients describing the short-run dynamics are insignificantly different from zero in all cases except in the ARMA(1,1) and the MA(1) models. In the former, the AR coefficient is not significant and thus, the MA(1) model seems to be more appropriate. In addition, both, the AIC and SIC give the highest values in this case. Therefore the best model specification for employment seems to be an ARIMA(0, 1.14, 1).

(Tables 3.c and 3.d about here)

3.d Unemployment rate

Again six models are selected in this series. The values of d oscillate now between -0.58 and 0.25 and the I(0) stationary hypothesis is not rejected in any of them. Looking at the most general specification, which is the ARMA(3,3) model, all except the first MA coefficient appear significant. The ARMA(2,2) model is clearly rejected, since all coefficients are insignificant, and eliminating here the second moving average component, the two AR coefficients are as well insignificant. We also see that both, the AR(3) and the AR(2) models give insignificant coefficients, suggesting that the AR(1) model might be more appropriate. In order to choose between the AR(1) and the ARMA(3,3), the AIC suggests the latter model, however, in view of the smaller number of parameters used in the AR(1) case, (leading to a higher value at the SIC), and the easier interpretation of the fractional differencing parameter d, (which also has an smaller standard error), we take the AR(1) model, choosing as a final specification for the unemployment rate, the ARIMA(1, 0.25, 0) model.

3.e Real wages

Ten models were considered when analyzing the real wages, with the values of d ranging from 1.16 through 1.41. Starting from the general case of an ARMA(3,1) model, we see that the last two AR coefficients are insignificantly different from zero. Going backwards to an ARMA(2,1), the second AR coefficient still remains insignificant, and in the ARMA(1,1) model, both parameters are close to zero. If we look at the AR(3) model, which is preferred to the ARMA(3,1) through a LR test, all parameters are insignificant, as is in the AR(2) and AR(1) cases. The ARMA(1,2) gives an insignificant second moving average coefficient and the MA(1) model also seems inappropriate. We can take the white noise model as the best specification to describe the short-run dynamics in this series, which also gives the smallest standard error for d and the highest values according to the AIC and the SIC. Thus, we can conclude the analysis of this series by saying that the real wages might be well described as an ARIMA(0, 1.22, 0) model.

(Tables 3.e and 3.f about here)

3.f Velocity

Five models are selected in this series and the values of d oscillate between 1.01 and 1.35. The ARMA(3,3) model gives various insignificant parameters. Eliminating first, the third and then the second MA coefficients, we still observe that the AR coefficients are not significantly different from zero. If we look at the ARMA(2,2) model, all the parameters are significant, as opposed to the ARMA(2,1) where the second AR parameter is not different from zero. Also the standard error of d is smaller under the previous parameterization. We conclude that the ARMA(2,2) model is the best of all these possible specifications, and thus, velocity might be well described as an ARIMA (2, 1.01, 2) model.

3.g Bond yield

This series requires special attention since any of the models passed the diagnostic tests at the 1% level, the main problem being due to the lack of normality of the residuals. A visual inspection of them suggests that this might be due to the presence of outliers during the World War II. One possibility is to work only on the post-war data, as we do with the remaining seven series below, but even taking only these data, we still have problems, finding now heteroscedastic residuals. Another possibility is to work on the logged series. (Note that this is the only unlogged series in Nelson and Plosser's (1982) data). However, we have decided to work with the same data set as they did. The approach adopted here consists of looking at the whole range of data, taking only those models which pass all the diagnostic tests at the 0.1% significance level. In doing so, we find three potential models, whose results are given in Table 3g. The values of d are 0.87 and 0.96 and the unit root hypothesis is not rejected in any of them. Looking at the ARMA(3,3) model, we observe insignificant parameters in both, the AR and the MA components. Performing LR tests, the ARMA(3,2) and the ARMA(2,3) specifications seem to be more appropriate. Taking the ARMA(3,2) model, the first AR and the first MA coefficients are insignificant, and taking an ARMA(2,3), only the first AR coefficient is significantly close to zero. The standard errors are much smaller in this model and the AIC and SIC also suggest that this might be the correct model specification. Therefore, we model this series as an ARIMA(2, 0.96, 3).

As mentioned just above, for the remaining seven series, all the estimated ARFIMA models failed to pass the diagnostic tests on the residuals, mainly because of the presence of outliers due to the World War II. Thus now ahead, we have decided to work only on the post-war data.

(Tables 3.g and 3.h about here)

3.h Nominal G.N.P.

Ten models were selected in this series according to the diagnostic tests on the residuals. We see that the values of d range now between 1.43 and 1.49, rejecting in all cases both, the I(0) and the I(1) hypotheses, and indicating clearly the nonstationary nature of the series. The most general specification is the ARMA(3,3) model, but we observe here that all the parameters are insignificantly different from zero. There is an improvement when we move backwards to an ARMA(3,1) model, where the last AR and the MA coefficients appear both significant. Going one step further we move to an AR(3) and the parameters change substantially with respect to the previous parameterization, with the first two coefficients significantly different from zero. A LR test indicates that this model is preferred rather than the ARMA(3,1), but the AR(2) model seems even a better modelization. Performing LR tests in order to decide between the AR(2), the AR(1) and the white noise specifications, evidence was found in favour of the AR(2) case. Also from the ARMA(3,1) model, we can move to an ARMA(2,1) and since the MA coefficient is not significantly different from zero, again the AR(2) model might be preferable. A MA(2) model has a second coefficient close to zero, suggesting that the MA(1) is a better fit, and similarly, from the ARMA(1,1), the MA(1) seems more appropriate. Therefore, we have to decide between the AR(2) and the MA(1) models. The AIC indicates that the AR(2) model is more adequate, but the SIC suggests the MA(1) specification. A visual inspection of the residuals indicates that the AR(2) specification gives residuals which are closer to white noise. Thus, we can conclude the analysis of the nominal G.N.P. by saying that it can be well described as an ARIMA(2, 1.49, 0) model.

3.i Industrial production

Eight models are selected in this series and the values of d range between 1.15 and 1.49. The ARMA(3,1) model appears worse than the ARMA(2,1), and also this appears worse than the MA(1) model, indicating the importance of the MA coefficient. Also evidence in favour of the MA(1) model is found from the MA(2) model, where the second coefficient appears insignificantly different from zero. On the other hand, an AR(3) model is clearly rejected in favour of an AR(2), and applying a LR test to choose between this and the AR(1) model, the former seems preferred. Therefore, we have, as in the previous case, to decide between the AR(2) and the MA(1) specifications, and since both, the AIC and SIC give higher values at the MA representation, the final model appears to be an ARIMA(0, 1.48, 1).

(Tables 3.i and 3.j about here)

3.j G.N.P. deflator

Only four models were adequate according to the diagnostic tests in this series and the values of d oscillate between 1.43 and 1.47, rejecting the unit root hypothesis in all cases. The ARMA(2,1) model is rejected since the AR coefficients are both insignificantly different from zero. Similarly, the

ARMA(1,1) model is also rejected because of the insignificance of the AR parameter. Choosing between the two final models (the AR(2) and the AR(1)), a LR test indicates that the AR(2) model should be preferred. This is also corroborated by the smaller standard errors observed in this model and the higher values obtained in both information criterions. Thus, we may conclude the analysis of this series by saying that the G.N.P. deflator may be well described as an ARIMA(2, 1.47, 0) model.

3.k Consumer prices

Nine models are selected to describe the consumer prices. The values of d range between 1.37 and 1.47. When modelling as an ARMA(3,2) process, the two MA coefficients are close to zero, and similarly, if we take an ARMA(3,1), the MA coefficient is significantly equal to zero. The AR(3) model seems to be appropriate, but comparing this with the AR(2) and AR(1) models, the test statistics suggest that the AR(2) representation might be more adequate. In addition, this model has smaller standard errors. A LR test was again performed to choose now between the ARMA(3,1) and the ARMA(2,1), and gave evidence in favour of the latter model, but the AR(2) specification appears again as a better fit. The MA(3) model has the last two coefficients close to zero and the MA(1) specification seems preferred, with a highly significant coefficient. Therefore, we have as final possible specifications the AR(2) and the MA(1) models. We take the MA(1) as the correct model specification, given the higher values observed under both, the AIC and the SIC. Thus, the consumer prices may be well described as an ARIMA(0, 1.39, 1).

(Tables 3.k and 3.l about here)

3.l Wages

Four models are selected in this series. The most general specification is an ARMA(3,1), but we observe that the first two AR coefficients in this model are not significantly different from zero. Moving to an ARMA(2,1) model, the first AR coefficient is still insignificant along with the MA coefficient. Deleting in this last model the MA component, the corresponding AR(2) model has again a first coefficient close to zero. It seems difficult to determine here which is the best model specification. A visual inspection of the residuals suggests that the AR(3) and the ARMA(3,1) models give the closest residuals to white noise, and performing a LR test to choose between these two models, the ARMA(3,1) specification seems preferred. Thus, the final model chosen is an ARIMA(3, 1.36, 1).

3.m Money stock

Five models are selected according to the diagnostic tests in this series and in all of them the values of d are 1.47 or 1.48. The most general specification, which is an ARMA(3,1), indicates that only the second AR coefficient is significantly equal to zero. Comparing this model with the AR(3), a LR test supports the latter model, though any of its coefficients appears now significant. Also this model is rejected in favour of the white noise specification. The MA(2) model has the second coefficient close to zero, and moving backwards to the MA(1), the coefficient becomes highly significant. Thus, we have to decide between the MA(1) and the white noise specification, and performing again a LR test, the MA(1) model appears more appropriate. This model also has the highest values at the AIC and SIC across all the possible specifications. We can conclude by saying that money stock may be well described as an ARIMA(0, 1.47, 1) model.

(Tables 3.m and 3.n about here)

3.n Common stock prices

Fourteen out of the sixteen ARMA representations passed all the diagnostic tests on the residuals. As in all the previous series, we start from the most general specification, which corresponds to the ARMA(3,3) model. In this specification only the first two MA coefficients are insignificantly different from zero. Going backwards from this model, either to an ARMA(3,2) or to an ARMA(2,3), in the former model both MA coefficients are close to zero, and in the latter only the last MA appears insignificant. Deleting this parameter and thus, moving to an ARMA(2,2) model, all the parameters are now significant. This model also seems more appropriate than the ARMA(2,1) and the ARMA(1,2). Similarly, the AR(3) model seems a better fit than the ARMA(3,1) and the ARMA(3,2), given the no-significance of the MA coefficients in the latter models. Performing LR tests to choose between the AR(3) and the AR(2), AR(1) and white noise specifications, the AR(3) appears the best one. The ARMA(1,1) model has an insignificant AR coefficient and the MA(1) appears more appropriate, which also seems an improvement over the MA(3) model. We have finally to decide between the ARMA(2,2), the AR(3) and the MA(1) models. In view of the lower standard errors and the highest value at the AIC across all the models presented, we conclude that the AR(3) model is the best possible specification to characterize the short-run dynamics in this series. Thus the final model for the common stock prices becomes an ARIMA(3, 1.46, 0).

Table 4 summarizes the best model specification for each series. We see that unemployment rate is the only series in which we cannot reject the hypothesis of I(0) stationary residuals (i.e., d = 0). For five of the series (real per capita G.N.P., employment, wages, velocity and bond yield), the unit root hypothesis (i.e., d = 1) is not rejected. For the remaining eight series, both hypotheses are clearly rejected, with all the integration orders greater than one. That means that even taking first differences, we still have significant dependence between observations widely separated in time.

(Table 4 about here)

According to these results, nominal G.N.P., industrial production, G.N.P. deflator, money stock, common stock prices and consumer prices are the most nonstationary series, with the unit root null hypothesis rejected in all of them; the unit root hypothesis is also rejected for real G.N.P. and real wages; real per capita G.N.P., employment, wages and velocity might be modelled with a unit root, though an order of integration greater than one is observed; the bond yield may also be modelled with a unit root, though the order of integration seems slightly smaller than one, and thus it may present a slight component of mean reversion. Finally, unemployment rate seems to be stationary, and though the I(0) hypothesis cannot be rejected, it could be better modelled with an order of integration greater than zero, and thus showing evidence of long memory. These results are in complete analogy with those given in Gil-Alaña and Robinson (1997) where it was shown that these series could be better characterized through fractional integration rather than with the classical I(1) and I(0) models. The only somewhat exceptional case that may deserve mention is industrial production where d is now equal to 1.48, while in Gil-Alaña and Robinson (1997) was showed to be close to stationarity.

The estimates of the remaining AR and MA parameters are also of interest. Consider, for instance, the unemployment rate, for which the model appears to be short memory (i.e., the estimated value of d is insignificantly different from zero). In this case, the short-run dynamic is described by an AR(1) model, which estimation yields to a parameter of 0.62, which implies that more than 95% of the effect of a shock will die away in approximately six years. If we allow d to be fractional rather than zero, and thus we suppose that this series might be better characterized with d = 0.25, the effect of a shock will also disappear, but it will take much more time.

Table 5 resumes the first seventeen impulse responses for the rates of growth of the series, except unemployment rate and bond yield (which are in levels), according to the previous model-selection criteria. We see that for the unemployment rate, the shock will tend to disappear in the long run, though even fifteen years later, still remains a 10% of its impact. This may illustrate the importance of distinguishing between short memory (d = 0) and long memory (d > 0) behaviours. For the bond yield, we observe that the shock seems to persist over time, though given that the estimated value of d is smaller than one, it will tend to disappear in the very long run. For the remaining twelve series, any shock in the growth rates will also tend to disappear though

(Table 5 about here)

at different rates. Thus, for example, for wages, 26.5% of the shock in its rate of growth still remains in the series after seventeen years; for industrial production 23%; for money, 15.8%; for G.N.P. deflator, 15.3%; and for consumer prices, 13.9%. These results corroborates the findings in Gil-Alaña and Robinson (1997) that these series were the most nonstationary ones, the only exception being again industrial production. On the other hand, almost 90% of the shock on the rates of growth of real wages, real per capita G.N.P., velocity and employment will disappear after three years.

4. Concluding remarks

Different ARFIMA(p,d,q) models have been proposed for an extended version of each of the Nelson and Plosser's (1982) series. In doing so we allow for a greater degree of flexibility in modelling the low-frequency dynamics than standard time series ARIMA(p,0,q) and ARIMA(p,1,q) representations, and permit to consider these models as special cases of this general specification.

Using the Sowell's (1992) procedure for estimating ARFIMA models by maximum likelihood in the time domain, we analyze carefully each of the series. Various models were first selected for each series according to several diagnostic tests on the residuals in order to assure that they were white noise. Then, a model-selection procedure, based on LR tests and other likelihood criterions was adopted to choose the best possible specification for each series. This is crucial when estimating with parametric approaches, since misspecification of the short run components of the series may invalidate the estimation of the fractional differencing parameter d.

The conclusions are that the unemployment rate is the only stationary series, with an order of integration of 0.25. The t-value on this parameter indicates that the I(0) stationary hypothesis cannot be rejected. For the remaining thirteen series, the results indicate that all them are nonstationary, with d ranging from 0.96 in the bond yield (and showing mean reversion) and 1.01 in velocity through 1.49 for the nominal G.N.P.. The unit root hypothesis is not rejected for bond yield, velocity, real per capita G.N.P., wages and employment. In all the other series, d appears to be much more greater than one and thus, the standard approach of taking first differences does not guarantee I(0) stationary residuals. In fact, the impulse response functions of the rates of growth of the series show that even ten years after the shock occur, almost 20% of its impact still remains for industrial production, G.N.P. deflator, wages, consumer prices and money stock, indicating clearly the long memory behaviour of these series.

Several other lines of research are under way which should prove relevant to the analysis of these and other macroeconomic data. Testing for instance the Bloomfield (1973) exponential spectral model for the description of the short-run components of the series, confounding with the fractional differencing was shown by Gil-Alaña and Robinson (1997) to be a credible alternative to the modelling of these series, though still its estimation in the context of fractional differencing needs to be studied. Semiparametric and non-parametric methods of estimating d in these series may also lead to a better understanding of their behaviour.

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TABLE 1

Maximum likelihood estimates of d in ARFIMA (p,d,q) models for the extended Nelson and Plosser data.

	ARMA(p,q)															
Series	(0,0)	(1,0)	(0,1)	(1,1)	(2,0)	(0,2)	(2,1)	(1,2)	(2,2)	(3,0)	(0,3)	(3,1)	(3,2)	(1,3)	(2,3)	(3,3)
Real G.N.P.	1.30'	1.17'	1.20'	1.17'	1.18'	1.15	1.49	--	1.49'	1.24'	1.19	1.49'	--	--	--	1.18
Nominal G.N.P.	1.39	1.26	1.28	1.27	1.29	1.28	1.48	1.48	1.31	1.32	--	1.42	1.47	1.48	--	1.29
Real per capita G.N.P.	1.24'	1.02'	1.09'	1.02'	1.03'	1.06	--'	1.49	1.11'	1.10'	1.07	1.49'	1.49'	1.49'	1.04	1.06
Industrial production	1.15	1.17	1.18	1.49	1.23	1.49	1.49	1.14	1.49	1.23	1.49	1.49	1.49	1.49	1.49	1.49
Employment	1.28	1.16	1.14'	1.17'	1.22'	1.21	1.21'	--	--	1.22'	1.48	1.21'	--	--	--	1.49
Unemployment rate	0.87	0.25	0.43	-0.42	-0.58'	0.40	-0.26'	-0.30	-0.28'	0.11'	0.31	-1.43	-1.38	-0.36	-1.45	-0.41'
G.N.P. deflator	1.40	1.29	1.32	1.28	1.28	--	1.28	1.32	1.35	1.29	--	1.32	1.27	1.28	1.36	1.32
Consumer prices	1.46	1.21	1.24	1.27	1.31	--	1.23	1.26	1.23	1.24	--	1.24	1.26	--	1.21	--
Wages	1.40	1.27	1.28	1.29	1.31	--	1.38	1.28	1.42	1.33	1.35	1.38	1.49	1.49	--	1.40
Real wages	1.22'	1.16'	1.16'	1.17'	1.21'	1.24'	1.41'	1.41'	1.38	1.24'	--	1.41'	--	1.41	1.41	1.42
Money stock	1.47	1.36	1.39	1.38	1.39	1.38	1.38	--	--	1.38	--	1.38	--	--	1.42	1.42
Velocity	1.07	0.99	0.99	1.00	1.00	0.97	1.34'	1.35	1.01'	1.06	1.38	1.34'	1.35'	1.34	1.36	1.35'
Bond yield	1.09	0.94	0.88	0.96	1.17	1.01	1.11	1.01	1.04	0.92	0.98	0.88	0.87	0.87	0.96	0.87
Common stock prices	1.12	1.00	1.12	1.01	1.08	1.09	1.07	--	1.42	1.08	1.42	1.07	1.42	1.42	1.42	1.45

--: The model failed to achieved convergence after 240 iterations.

': The corresponding model passed all the diagnostic tests of normality, heteroscedasticity, ARCH and Lunj & Box at the 1% significance level.

TABLE 2

Maximum likelihood estimates of d in ARFIMA (p,d,q) models for the extended Nelson and Plosser data, starting in 1947.

	ARMA(p,q)															
Series	(0,0)	(1,0)	(0,1)	(1,1)	(2,0)	(0,2)	(2,1)	(1,2)	(2,2)	(3,0)	(0,3)	(3,1)	(3,2)	(1,3)	(2,3)	(3,3)
Real G.N.P.	1.33	1.31’	1.31	1.31	1.34’	--	1.34’	1.33	--	1.30’	1.23	1.31’	1.32	--	1.27	1.30
Nominal G.N.P.	1.43’	1.47’	1.49’	1.49’	1.49’	1.48’	1.49’	1.47	1.47	1.48’	1.48	1.48’	--	--	1.47	1.47’
Real per capita G.N.P.	1.24	1.17’	1.17	1.20	1.19’	1.20	1.20’	--	1.40	1.14’	--	1.14’	1.15	--	--	1.34
Industrial production	1.15’	1.24’	1.48’	1.49	1.36’	1.49’	1.48’	1.49	--	1.38’	1.48	1.49’	1.49	1.48	--	1.49
Employment	1.31	1.26’	1.21	1.25’	1.38’	1.40	1.36’	--	1.36	1.34’	--	1.34’	1.26	--	1.39	--
Unemployment rate	0.79	0.62’	0.59	0.65	0.80’	0.77	0.78’	1.41	0.76	0.75	1.42	0.75	0.64’	--	1.49	1.42’
G.N.P. deflator	1.48	1.43’	1.45	1.44’	1.47’	1.43	1.46’	1.44	1.46	1.39	1.43	1.38	1.38	1.45	1.44	1.40
Consumer prices	1.47’	1.41’	1.39’	1.40	1.47’	1.41	1.46’	1.44	--	1.41’	1.44’	1.38’	1.37	1.44	1.44	--
Wages	1.46	1.47	1.48	1.48	1.48’	--	1.48’	1.48	--	0.93’	--	1.36’	1.36	1.45	--	1.39
Real wages	1.30’	1.06’	1.12’	1.17’	1.17’	--	1.08’	1.15	0.62’	1.17’	--	0.65’	1.16	1.08	--	1.18
Money stock	1.48’	1.46	1.47’	1.47	1.48	1.47’	1.48	1.48	1.47	1.48’	1.48	1.48’	--	--	1.48	1.48
Velocity	1.00	0.97	0.81	0.93	1.26	1.30	1.18	1.31	1.06’	1.09	1.25	1.10’	--	1.31	1.13’	--
Bond yield	1.09	0.94	0.88	0.95	1.17	1.02	1.12	1.02	1.06	0.96	1.01	0.92	0.90	0.92	1.00	0.90
Common stock prices	1.19’	1.24’	1.42’	1.42’	1.36’	1.42	1.43’	1.42’	1.39’	1.46’	1.40’	1.45’	1.43’	1.26	1.40’	1.42’

--: The model failed to achieved convergence after 240 iterations.
’: The corresponding model passed all the diagnostic tests of normality, heteroscedasticity, ARCH and Lunj & Box at the 1% significance level.

TABLE 3.a*

Parameter estimates of ARFIMA models for real G.N.P.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,0)	1.30 (0.08)	16.25	3.75	--	--	--	--	--	--	225.50	223.13
(1,0)	1.17 (0.11)	10.63	1.54	0.25 (0.16)	--	--	--	--	--	226.06	221.32
(0,1)	1.20 (0.09)	13.33	2.22	--	--	--	0.21 (0.10)	--	--	226.01	221.28
(1,1)	1.17 (0.11)	10.63	1.54	0.15 (0.37)	--	--	0.09 (0.32)	--	--	224.16	217.65
(2,0)	1.18 (0.11)	10.72	1.63	0.24 (0.16)	-0.05 (0.11)	--	--	--	--	224.28	217.17
(2,2)	1.49 (0.01)	149.0	49.0	1.16 (0.39)	-0.43 (0.28)	--	-1.34 (0.41)	0.36 (0.41)	--	227.08	215.23
(3,0)	1.24 (0.11)	11.27	2.18	0.24 (0.11)	0.18 (0.15)	-0.03 (0.11)	--	--	--	224.26	214.79
(3,1)	1.49 (0.01)	149.0	49.0	0.77 (0.11)	-0.09 (0.14)	-0.11 (0.11)	-0.97 (0.12)	--	--	227.37	215.51

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis. The AIC is $2L_i - 2N_i$ and the SIC is $2L_i - N_i \ln T_i$, where L_i is the log likelihood; N_i is the number of parameters and T_i is the sample size.

TABLE 3.b*

Parameter estimates of ARFIMA models for real G.N.P. per capita.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,0)	1.24 (0.10)	12.40	2.40	--	--	--	--	--	--	224.72	222.35
(1,0)	1.02 (0.14)	7.28	0.14	0.34 (0.18)	--	--	--	--	--	226.92	222.18
(0,1)	1.09 (0.10)	10.90	0.90	--	--	--	0.27 (0.12)	--	--	226.54	221.80
(1,1)	1.02 (0.14)	7.28	0.14	0.25 (0.31)	--	--	0.09 (0.25)	--	--	225.07	217.96
(2,0)	1.03 (0.14)	7.35	0.21	0.35 (0.18)	-0.05 (0.11)	--	--	--	--	225.19	218.07
(2,2)	1.11 (0.09)	12.33	1.22	0.81 (0.10)	-0.89 (0.08)	--	-0.65 (0.11)	0.98 (0.18)	--	229.45	217.60
(3,0)	1.10 (0.13)	8.46	0.76	0.28 (0.17)	-0.02 (0.11)	-0.15 (0.11)	--	--	--	224.86	215.38
(3,1)	1.49 (0.05)	29.80	9.80	0.77 (0.11)	-0.09 (0.14)	-0.10 (0.11)	-0.97 (0.15)	--	--	225.94	214.09
(3,2)	1.49 (0.05)	29.80	9.80	0.69 (1.12)	-0.02 (0.90)	-0.11 (0.21)	-0.89 (1.12)	-0.08 (1.11)	--	223.95	209.72

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.c*

Parameter estimates of ARFIMA models for employment.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,1)	1.14 (0.08)	14.25	1.75	--	--	--	0.33 (0.12)	--	--	379.61	374.43
(1,1)	1.17 (0.09)	13.00	1.88	-0.20 (0.29)	--	--	0.48 (0.22)	--	--	378.05	370.28
(2,0)	1.22 (0.10)	12.20	2.20	0.21 (0.14)	-0.18 (0.10)	--	--	--	--	378.43	370.67
(2,1)	1.21 (0.10)	12.10	2.10	-0.01 (0.51)	0.12 (0.18)	--	0.24 (0.54)	--	--	376.51	366.16
(3,0)	1.22 (0.11)	11.09	2.00	0.21 (0.15)	-0.18 (0.10)	0.008 (0.11)	--	--	--	376.43	366.09
(3,1)	1.21 (0.11)	11.00	1.90	-0.10 (0.83)	-0.10 (0.21)	-0.02 (0.19)	0.33 (0.81)	--	--	374.53	361.61

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.d*

Parameter estimates of ARFIMA models for unemployment rate.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(1,0)	0.25	1.04	-3.12	0.62	--	--	--	--	--	-112.13	-117.29
	(0.24)			(0.18)							
(2,0)	-0.58	-0.77	-2.10	1.43	-0.52	--	--	--	--	-109.18	-116.94
	(0.75)			(0.62)	(0.49)						
(2,1)	-0.26	-0.92	-4.50	0.59	0.17	--	0.71	--	--	-103.92	-114.25
	(0.28)			(0.36)	(0.22)		(0.14)				
(2,2)	-0.28	-0.87	-4.00	0.53	0.22	--	0.78	0.05	--	-105.90	-118.82
	(0.32)			(0.64)	(0.51)		(0.72)	(0.47)			
(3,0)	0.11	0.25	-2.06	0.90	-0.37	0.18	--	--	--	-108.64	-118.97
	(0.43)			(0.38)	(0.17)	(0.10)					
(3,3)	-0.41	-1.51	-5.22	1.15	-1.00	0.59	0.27	0.57	0.60	-106.71	-124.79
	(0.27)			(0.43)	(0.39)	(0.18)	(0.26)	(0.17)	(0.11)		

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.e*

Parameter estimates of ARFIMA models for real wages.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,0)	1.22	17.42	3.14	--	--	--	--	--	--	333.49	331.00
	(0.07)										
(1,0)	1.16	11.60	1.60	0.11	--	--	--	--	--	332.14	327.18
	(0.10)			(0.14)							
(0,1)	1.16	12.88	1.77	--	--	--	0.14	--	--	332.36	327.40
	(0.09)						(0.14)				
(1,1)	1.17	13.00	1.88	-0.26	--	--	0.39	--	--	330.54	323.10
	(0.09)			(0.68)			(0.62)				
(2,0)	1.21	12.10	2.10	0.08	-0.10	--	--	--	--	331.00	323.56
	(0.10)			(0.15)	(0.11)						
(0,2)	1.24	7.75	1.50	--	--	--	0.03	-0.12	--	330.92	323.48
	(0.16)						(0.23)	(0.18)			
(2,1)	1.41	12.81	3.72	0.66	-0.12	--	-0.82	--	--	331.32	321.41
	(0.11)			(0.15)	(0.11)		(0.13)				
(1,2)	1.41	12.81	3.72	0.48	--	--	-0.65	-0.15	--	331.22	321.31
	(0.11)			(0.21)			(0.24)	(0.14)			
(3,0)	1.24	11.27	2.18	0.04	-0.11	-0.07	--	--	--	329.44	319.53
	(0.11)			(0.15)	(0.11)	(0.11)					
(3,1)	1.41	12.81	3.72	0.65	-0.11	-0.02	-0.81	--	--	329.35	316.95
	(0.11)			(0.16)	(0.12)	(0.11)	(0.15)				

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.f*

Parameter estimates of ARFIMA models for velocity.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(2,1)	1.34	7.44	1.88	0.60	-0.10	--	-0.83	--	--	313.63	302.50
	(0.18)			(0.16)	(0.10)		(0.10)				
(2,2)	1.01	14.42	0.14	0.89	-0.83	--	-0.76	0.76	--	312.21	298.30
	(0.07)			(0.20)	(0.16)		(0.21)	(0.26)			
(3,1)	1.34	7.88	2.00	0.53	-0.03	-0.14	-0.78	--	--	313.72	299.82
	(0.17)			(0.14)	(0.10)	(0.10)	(0.15)				
(3,2)	1.35	7.50	1.94	0.79	-0.20	-0.13	-1.05	0.23	--	312.03	295.34
	(0.18)			(0.45)	(0.30)	(0.11)	(0.48)	(0.38)			
(3,3)	1.35	7.94	2.05	0.40	0.35	-0.35	-0.65	-0.43	0.28	309.98	290.52
	(0.17)			(0.48)	(0.45)	(0.23)	(0.55)	(0.53)	(0.36)		

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.g*

Parameter estimates of ARFIMA models for bond yield.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(3,2)	0.87	3.78	-0.56	0.21	-0.75	0.54	0.16	0.75	--	-153.91	-168.76
	(0.23)			(0.24)	(0.11)	(0.23)	(0.13)	(0.11)			
(2,3)	0.96	9.60	-0.40	-0.06	-0.86	--	0.33	0.92	0.49	-153.19	-168.04
	(0.10)			(0.07)	(0.07)		(0.10)	(0.08)	(0.11)		
(3,3)	0.87	3.78	-0.56	0.11	-0.78	0.41	0.29	0.79	0.18	-155.13	-172.46
	(0.23)			(0.33)	(0.13)	(0.33)	(0.19)	(0.10)	(0.21)		

*: All these models passed the diagnostic tests on the residuals at the 0.1% significance level. Standard errors in parenthesis.

TABLE 3.h*

Parameter estimates of ARFIMA models for nominal G.N.P., starting from 1947.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,0)	1.43	28.60	8.60	--	--	--	--	--	--	155.50	153.73
	(0.05)										
(1,0)	1.47	49.00	15.66	-0.31	--	--	--	--	--	156.62	153.09
	(0.03)			(0.16)							
(0,1)	1.49	149.0	49.00	--	--	--	-0.46	--	--	159.54	156.01
	(0.01)						(0.13)				
(1,1)	1.49	149.0	49.00	-0.003	--	--	-0.46	--	--	157.54	152.25
	(0.01)			(0.26)			(0.20)				
(2,0)	1.49	149.0	49.00	-0.46	-0.41	--	--	--	--	161.03	155.73
	(0.01)			(0.15)	(0.15)						
(0,2)	1.48	148.0	48.00	--	--	--	-0.47	-0.008	--	157.54	152.25
	(0.01)						(0.26)	(0.27)			
(2,1)	1.49	149.0	49.00	-0.54	-0.43	--	0.09	--	--	159.10	152.05
	(0.01)			(0.34)	(0.17)		(0.36)				
(3,0)	1.48	148.0	48.00	-0.44	-0.38	0.05	--	--	--	159.13	152.07
	(0.01)			(0.16)	(0.17)	(0.17)					
(3,1)	1.48	49.33	16.00	0.27	-0.04	0.38	-0.69	--	--	157.64	148.83
	(0.03)			(0.38)	(0.21)	(0.18)	(0.35)				
(3,3)	1.47	49.00	15.66	0.24	-0.004	0.22	-0.68	-0.04	0.17	153.89	141.55
	(0.03)			(0.62)	(0.60)	(0.50)	(0.59)	(0.77)	(0.63)		

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.i*

Parameter estimates of ARFIMA models for industrial production, starting from 1947.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,0)	1.15 (0.08)	14.37	1.87	--	--	--	--	--	--	106.42	104.65
(1,0)	1.24 (0.10)	12.40	2.40	-0.25 (0.19)	--	--	--	--	--	105.90	102.37
(0,1)	1.48 (0.02)	74.00	24.00	--	--	--	0.84 (0.12)	--	--	111.34	107.81
(2,0)	1.36 (0.09)	15.11	4.00	-0.49 (0.18)	-0.39 (0.16)	--	--	--	--	108.39	103.09
(0,2)	1.49 (0.01)	149.0	49.00	--	--	--	-0.72 (0.21)	-0.14 (0.22)	--	109.82	104.53
(2,1)	1.48 (0.02)	74.00	24.00	0.08 (0.21)	-0.13 (0.20)	--	0.82 (0.18)	--	--	108.94	101.07
(3,0)	1.38 (0.10)	13.80	3.80	-0.47 (0.20)	-0.42 (0.19)	-0.05 (0.18)	--	--	--	106.46	99.41
(3,1)	1.49 (0.02)	74.50	24.50	0.19 (0.25)	-0.10 (0.21)	0.18 (0.22)	-0.92 (0.25)	--	--	106.83	98.01

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.j*

Parameter estimates of ARFIMA models for G.N.P. deflator, starting from 1947.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(1,0)	1.43	17.87	5.37	0.51	--	--	--	--	--	209.72	206.16
	(0.08)			(0.17)							
(1,1)	1.44	24.00	7.33	0.12	--	--	0.60	--	--	214.37	209.07
	(0.06)			(0.22)			(0.13)				
(2,0)	1.47	49.00	15.66	0.60	-0.36	--	--	--	--	212.43	207.13
	(0.03)			(0.15)	(0.16)						
(2,1)	1.46	29.20	9.20	0.21	-0.16	--	0.50	--	--	212.89	205.83
	(0.05)			(0.25)	(0.22)		(0.22)				

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.k*

Parameter estimates of ARFIMA models for consumer prices, starting from 1947.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,0)	1.47 (0.03)	49.00	15.66	--	--	--	--	--	--	182.10	180.33
(1,0)	1.41 (0.09)	15.66	4.55	0.39 (0.17)	--	--	--	--	--	185.72	182.19
(0,1)	1.39 (0.07)	19.85	5.57	--	--	--	0.77 (0.13)	--	--	196.29	192.75
(2,0)	1.47 (0.03)	49.00	15.66	0.51 (0.13)	-0.53 (0.14)	--	--	--	--	193.99	188.69
(2,1)	1.46 (0.04)	36.50	11.50	0.17 (0.21)	-0.40 (0.18)	--	0.51 (0.20)	--	--	195.81	188.75
(3,0)	1.41 (0.13)	10.84	3.15	0.73 (0.22)	-0.69 (0.16)	0.41 (0.21)	--	--	--	196.66	189.61
(0,3)	1.44 (0.06)	24.00	7.33	--	--	--	0.75 (0.17)	-0.12 (0.20)	-0.27 (0.15)	195.06	188.01
(3,1)	1.38 (0.18)	7.66	2.11	1.02 (0.44)	-0.85 (0.29)	0.54 (0.22)	-0.29 (0.46)	--	--	194.81	185.99
(3,2)	1.37 (0.22)	6.22	1.68	0.98 (0.33)	-0.69 (0.31)	0.48 (0.20)	-0.19 (0.31)	-0.19 (0.24)	--	193.40	182.83

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.1*

Parameter estimates of ARFIMA models for wages, starting from 1947.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(2,0)	1.48	148.0	48.00	-0.21	-0.30	--	--	--	--	194.24	188.95
	(0.01)			(0.17)	(0.17)						
(2,1)	1.48	148.0	48.00	-0.48	-0.37	--	0.28	--	--	192.96	185.91
	(0.01)			(0.34)	(0.16)		(0.32)				
(3,0)	0.93	5.16	-0.38	0.38	0.006	0.58	--	--	--	196.46	189.41
	(0.18)			(0.20)	(0.18)	(0.16)					
(3,1)	1.36	5.23	1.38	0.37	-0.11	0.55	-0.47	--	--	196.61	187.79
	(0.26)			(0.24)	(0.18)	(0.16)	(0.19)				

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.m*

Parameter estimates of ARFIMA models for money stock, starting from 1947.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,0)	1.48 (0.01)	148.0	48.00	--	--	--	--	--	--	198.53	196.75
(0,1)	1.47 (0.03)	49.00	15.66	--	--	--	0.34 (0.13)	--	--	200.60	197.07
(0,2)	1.47 (0.04)	36.75	11.75	--	--	--	0.32 (0.24)	-0.02 (0.21)	--	198.61	193.31
(3,0)	1.48 (0.01)	148.0	48.00	0.29 (0.16)	-0.28 (0.16)	-0.03 (0.16)	--	--	--	198.51	191.45
(3,1)	1.48 (0.01)	148.0	48.00	-0.54 (0.18)	-0.02 (0.18)	-0.39 (0.15)	0.86 (0.14)	--	--	199.37	190.55

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 3.n*

Parameter estimates of ARFIMA models for common stock prices, starting from 1947.

ARMA	d	$t_{d=0}$	$t_{d=1}$	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SIC
(0,0)	1.19	13.22	2.11	--	--	--	--	--	--	52.42	50.65
	(0.09)										
(1,0)	1.24	11.27	2.18	-0.12	--	--	--	--	--	50.79	47.25
	(0.11)			(0.19)							
(0,1)	1.42	14.20	4.20	--	--	--	-0.50	--	--	52.64	49.11
	(0.10)						(0.19)				
(1,1)	1.42	14.20	4.20	0.19	--	--	-0.62	--	--	51.25	45.95
	(0.10)			(0.26)			(0.22)				
(2,0)	1.36	15.11	4.00	-0.27	-0.34	--	--	--	--	52.76	47.47
	(0.09)			(0.17)	(0.15)						
(2,1)	1.43	20.42	6.17	-0.05	-0.34	--	-0.35	--	--	52.45	45.39
	(0.07)			(0.23)	(0.16)		(0.23)				
(1,2)	1.42	14.20	4.20	-0.13	--	--	-0.24	-0.22	--	50.02	42.97
	(0.10)			(0.43)			(0.42)	(0.20)			
(2,2)	1.39	13.90	3.90	0.40	-0.74	--	-0.84	0.73	--	55.67	46.85
	(0.10)			(0.20)	(0.15)		(0.17)	(0.23)			
(3,0)	1.46	36.50	11.50	-0.49	-0.51	-0.38	--	--	--	55.98	48.93
	(0.04)			(0.15)	(0.14)	(0.14)					
(0,3)	1.40	14.00	4.00	--	--	--	-0.60	-0.07	0.37	52.32	45.27
	(0.10)						(0.17)	(0.14)	(0.15)		
(3,1)	1.45	29.00	9.00	-0.73	-0.59	-0.47	0.29	--	--	54.82	46.01
	(0.05)			(0.29)	(0.17)	(0.15)	(0.32)				
(3,2)	1.43	17.87	5.37	-0.67	-0.74	-0.48	0.27	0.26	--	53.60	43.03
	(0.08)			(0.32)	(0.21)	(0.16)	(0.39)	(0.27)			
(2,3)	1.40	12.72	3.63	0.40	-0.75	--	-0.85	0.74	-0.01	53.67	43.09
	(0.11)			(0.21)	(0.17)		(0.26)	(0.33)	(0.20)		
(3,3)	1.42	17.75	5.25	-0.57	-0.41	-0.73	0.09	-0.02	0.59	53.03	40.69
	(0.08)			(0.23)	(0.22)	(0.15)	(0.25)	(0.21)	(0.28)		

*: All these models passed the diagnostic tests on the residuals at the 1% significance level. Standard errors in parenthesis.

TABLE 4

Best model specification for the extended version of Nelson and Plosser's data set.

Series	ARFIMA(p,d,q)	$t_{d=0}$	$t_{d=1}$	AR estimates ϕ_1	ϕ_2	ϕ_3	MA estimates θ_1	θ_2	θ_3
Real G.N.P.	(0, 1.30, 0)	16.25	3.75	--	--	--	--	--	--
Nominal G.N.P.*	(2, 1.49, 0)	149.0	49.00	-0.46	-0.41	--	--	--	--
Real per capita G.N.P.	(2, 1.11, 2)	12.33	1.22'	0.81	-0.89	--	-0.65	0.89	--
Industrial production*	(0, 1.48, 1)	74.00	24.00	--	--	--	0.84	--	--
Employment	(0, 1.14, 1)	14.25	1.75'	--	--	--	0.33	--	--
Unemployment rate	(1, 0.25, 0)	1.04'	-3.12	0.62	--	--	--	--	--
G.N.P. deflator*	(2, 1.47, 0)	49.00	15.66	0.60	-0.36	--	--	--	--
Consumer prices*	(0, 1.39, 1)	19.85	5.57	--	--	--	0.77	--	--
Wages*	(3, 1.36, 1)	5.23	1.38'	0.37	-0.11	0.55	-0.47	--	--
Real wages	(0, 1.22, 0)	17.42	3.14	--	--	--	--	--	--
Money stock*	(0. 1.47, 1)	49.00	15.66	--	--	--	0.34	--	--
Velocity	(2, 1.01, 2)	14.42	0.14'	0.89	-0.83	--	-0.76	0.76	--
Bond yield	(2, 0.96, 3)	9.60	-0.40'	-0.06	-0.86	--	0.33	0.92	0.49
Common stock prices*	(3, 1.46, 0)	36.50	11.50	-0.49	-0.51	-0.38	--	--	--

*: These series were analyzed using only the post-war data. ': Non-rejection values of the null hypothesis: d = 0 and d = 1.

TABLE 5

Impulse response functions for the growth rate in the extended version of Nelson and Plosser's data set.

Series	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Real G.N.P.	.300	.195	.149	.123	.106	.093	.084	.076	.070	.065	.061	.058	.055	.052	.049	.047	.045
Nominal G.N.P.	.030	-.058	.317	.142	.041	.139	.120	.070	.093	.094	.079	.078	.079	.073	.071	.070	.067
Real p.capita G.N.P.	.270	.208	.029	-.101	-.064	.073	.146	.079	-.043	-.085	-.011	.083	.093	.016	-.056	-.047	.024
Ind. production	1.319	.758	.591	.502	.443	.401	.369	.343	.322	.304	.289	.276	.265	.254	.245	.237	.230
Employment	.470	.126	.083	.063	.051	.043	.038	.033	.030	.028	.025	.023	.022	.020	.019	.018	.017
Unemployment rate	.870	.695	.548	.435	.350	.288	.241	.207	.181	.160	.145	.132	.122	.113	.106	.100	.094
G.N.P. deflator	1.070	.627	.275	.186	.233	.273	.266	.234	.208	.195	.189	.184	.177	.169	.163	.158	.153
Consumer prices	1.159	.571	.424	.349	.301	.268	.242	.223	.207	.193	.182	.173	.164	.157	.150	.144	.139
Wages	.260	.061	.621	.437	.192	.424	.431	.270	.334	.377	.294	.292	.322	.286	.267	.279	.265
Real wages	.219	.134	.099	.079	.067	.058	.052	.047	.042	.039	.036	.034	.032	.030	.028	.027	.026
Money stock	.810	.505	.401	.343	.304	.276	.254	.236	.222	.210	.199	.190	.182	.175	.169	.163	.158
Velocity	.139	.052	-.062	-.095	-.030	.054	.075	.023	-.040	-.054	-.013	.033	.042	.010	-.025	-.030	-.005
Bond yield	1.229	1.243	1.479	1.402	1.173	1.229	1.405	1.330	1.711	1.233	1.356	1.286	1.176	1.235	1.319	1.257	1.182
C. stock prices	-.030	-.159	-.011	.336	.113	-.029	.007	.134	.098	.028	.025	.070	.070	.043	.035	.048	.053

*: All the series are in first differences except unemployment rate and bond yield.

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